


# Explainable AI Modeling of Special Education Teachers' Psychological Well-Being During Artificial Intelligence Integration: The Roles of Occupational Stress, Self-Regulation, and Technological Confidence

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## 1. Round 1

### 1.1. Reviewer 1

Reviewer:

The Introduction cites a broad range of studies related to special education, inclusion, teacher preparation, family involvement, and technology; however, the paragraph beginning “Despite the growing body of literature addressing teacher stress, technological adaptation, and instructional innovation” should more sharply identify the specific empirical gap. The current gap statement is relevant but general. The authors should explicitly state whether the novelty of the study lies in focusing on special education teachers, examining AI integration, using explainable AI, comparing machine-learning models, or integrating occupational and psychological predictors. A more precise gap statement would help justify why the study is necessary and how it advances existing knowledge.

The Methods section states that “The present study was conducted using a quantitative, cross-sectional, predictive-correlational design with an explainable artificial intelligence modeling approach.” This sentence is appropriate, but the authors should clarify how a cross-sectional design supports predictive modeling without implying causality. Throughout the

manuscript, terms such as “predictor,” “influence,” and “contribution” are used frequently. The authors should explicitly state that prediction in this study refers to statistical and machine-learning prediction rather than temporal or causal prediction. This clarification is essential because occupational stress, self-regulation, technological confidence, and psychological well-being were measured at the same time point.

In the Study Design and Participants paragraph, the manuscript reports that “The final sample included 318 special education teachers from Tehran who were selected through multistage cluster sampling.” This is an important methodological claim, but the sampling process is not described with sufficient operational detail. The authors should specify how many educational districts were selected, how many schools were approached, how many teachers were invited, how many declined participation, and how the final sample size of 318 was determined. A flow of recruitment and inclusion would strengthen transparency and allow readers to evaluate possible selection bias.

Table 3 reports that extreme gradient boosting achieved a test  $R^2$  of 0.73 and the lowest prediction error. This result is promising, but the manuscript should interpret the improvement over linear regression carefully. The sample size is not large, and the number of predictors appears limited. Therefore, the authors should explain why a complex boosting model is justified over a more parsimonious linear model. They should also report whether the performance difference between models was statistically or practically meaningful, rather than relying only on point estimates of  $R^2$ , MAE, and RMSE.

In the paragraph interpreting Table 3, the manuscript states that “The difference between training and test performance was not excessive, suggesting that the selected model achieved a reasonable balance between model fit and generalizability.” This claim should be supported more rigorously. The training  $R^2$  for extreme gradient boosting is 0.84 and the test  $R^2$  is 0.73, which may be acceptable, but the authors should report cross-validation variability, such as standard deviations or confidence intervals around RMSE and  $R^2$ . Without variability estimates, it is difficult to determine whether the model generalizes reliably.

Authors revised and uploaded the document.

## 1.2. Reviewer 2

Reviewer:

The participant description reports that teachers were selected from “public and non-public exceptional schools in Tehran,” but the manuscript should clarify whether these schools are administered under the same special education authority and whether differences in institutional resources were considered. Public and non-public special education schools may differ in class size, access to educational technology, professional development opportunities, workload, and family expectations. Since school type was included as a background variable in the SHAP analysis, the manuscript should provide a stronger rationale for its inclusion and describe how it was coded in the dataset.

The Methods section states that inclusion criteria included “recent exposure to digital or artificial intelligence-based educational tools.” This criterion requires greater precision. The authors should define “recent exposure” using a specific time frame, such as exposure within the previous semester or academic year. They should also explain how exposure was verified: through self-report, school records, participation in training, or actual use of specific tools. Without a clear operational definition, participants with very different levels of AI familiarity may have been grouped together, which could reduce the interpretability of the findings.

In the Data Collection Tools section, the manuscript states that the Computer Self-Efficacy Scale was “adapted to reflect the use of educational technologies and artificial intelligence-supported tools in teaching.” This adaptation is potentially valuable, but it raises psychometric concerns. The authors should describe the adaptation procedure in detail, including translation if applicable, expert review, content validity assessment, pilot testing, and any changes made to item wording. Since changing items may alter the factor structure and validity of the original instrument, the authors should report whether exploratory or confirmatory factor analysis was conducted for the adapted version.

The description of the Ryff Psychological Well-Being Scale notes that “the 42-item version of the scale was used because it provides an appropriate balance between conceptual coverage and practical applicability.” This justification is acceptable but

incomplete. The authors should specify the response scale, scoring range, number of reverse-scored items, and whether the total score or six subscale scores were used in the analyses. Because the theoretical construct is multidimensional, the decision to use only the total score should be justified. It would also be useful to explain whether any subdimensions of psychological well-being were especially relevant to AI integration, such as environmental mastery or personal growth.

The Teacher Stress Inventory is described as including multiple sources and manifestations of stress, but the manuscript reports only a total occupational stress score. The authors should justify why the total score was used rather than subscale scores. In the context of AI integration, certain stress domains, such as time management, professional distress, and fatigue manifestations, may be more relevant than others. Examining subdomains could provide a more nuanced understanding of which aspects of occupational stress are most harmful to psychological well-being among special education teachers.

The Data Analysis section states that “The dataset was divided into training and testing subsets, with 80% of the data used for model training and 20% used for model testing.” Given the moderate sample size of 318, the authors should justify the 80/20 split and describe whether the split was random, stratified, or repeated. A single random train-test split may produce unstable model performance estimates in small to moderate datasets. The authors should consider using repeated k-fold cross-validation or nested cross-validation to provide more robust and less sample-dependent performance estimates.

The machine-learning procedure reports that “Hyperparameter tuning was performed to optimize model performance,” but no details are provided about the hyperparameter search. The authors should report which parameters were tuned for random forest, gradient boosting, support vector regression, and extreme gradient boosting, what search strategy was used, what ranges were tested, and whether tuning was conducted only within the training set. This information is essential to assess reproducibility and to ensure that no information from the test set was inadvertently used during model optimization.

In the Findings section, Table 2 reports that the regression model explained 58.7% of the variance in psychological well-being, with self-regulation, occupational stress, and technological confidence as significant predictors. This is a strong result, but the manuscript should report regression diagnostics more completely. The authors mention VIF values but should also provide evidence regarding residual normality, homoscedasticity, influential cases, and independence of errors. Given that the dependent variable is a psychological scale score, diagnostic plots or additional statistics would help support the validity of the regression interpretation.

Authors revised and uploaded the document.

## 2. Revised

Editor’s decision after revisions: Accepted.

Editor in Chief’s decision: Accepted.